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Predicting the Need to Perform Life-Saving Interventions in Trauma Patients Using New Vital Signs and Artificial Neural Networks

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Objective

To evaluate whether descriptive data derived from EKG analysis and submitted to off-the-shelf ANN software could be used for identification of individuals who received life-saving interventions in a mixed cohort of prehospital and emergency trauma patients.

Hypothesis

ANN reliably identifies patients who received an LSI based on EKG-derived new vital signs.

Methods

- Patients were identified for this study using the Trauma Vitals database developed by the U.S. Army Institute of Surgical Research (Fort Sam Houston, TX).
- Commercial monitors used for EKG and vital sign data collection (Pic 50^{TM} vital sign monitor, Welch Allyn, Inc., Skaneateles Falls, NY and ProPaq monitor (Welch Allyn, Inc., Skaneateles Falls, NY).
- Conventional vital signs, mechanism of injury (MOI, blunt or penetrating), field Glasgow Coma Scale score (GCS), age, sex, and in-hospital mortality were recorded. Blood pressures were measured automatically by cuff using the vital signs monitor.
- Retrospective review of 10-30 minute-long EKG sections and clinical data from 464 patients.
- Patients were included into the study if: 1) their EKG was present and without electromechanical noise; 2) 800 R-to-R intervals (RRIs) were available for analysis; 3) no ectopic beats were found within the analyzed data segments.
- EKGs were analyzed off-line using the WinCPRs software (Absolute Aliens Inc., Turku, Finland) as previously described [Batchinsky et al., J Trauma 2007].
- The ANN used was a commercially available feed-forward back-propagation ANN (NeuralWare, Carnegie, PA). The software was used in its default settings with training on 70% of the data and analysis on 30%. A 10-fold cross-validation was performed.
- SAS version 9.1 (SAS Institute, Cary, NC) was used for statistical analysis.

Results

Table 1. Demographics, conventional vital signs and injury scores.

Variable	Non LSI (n=197)	LSI (n=65)	p value
Age, yr	35.30 ± 0.99	33.50 ± 1.80	0.271
Sex (male)	75.10%	82.50%	0.224
MOI (penetrating)	28.42%	26.56%	0.775
HR	97 ± 1.60	109 ± 4.30	0.004
SAP	129 ± 1.70	120 ± 3.60	0.03
GCS_{TOTAL}	14.20 ± 0.16	8.94± 0.70	<.0001
GCS_{MOTOR}	5.80 ± 0.06	3.70 ± 0.32	<.0001
Mortality	1.52%	13.90%	0.0004

LSI, patients that received lifesaving interventions; Non LSI, patients that did not receive LSIs; MOI, mechanism of injury (percentage of penetrating injuries); HR, heart rate, beats per minute; SAP, systolic arterial pressure, mm HG; $GCS_{TOTAL,}$ field Glasgow Coma Score total; $GCS_{MOTOR,}$ field Glasgow Coma Score motor. Data are means ± SEM.

Table 2. Linear time- and frequency-domain analysis variables associated with the need to perform life-saving interventions by ANN.

Variable	Non LSI (n=197)	LSI (n=65)	p value	Reflects parasympathetic nervous system	Reflects sympathetic nervous system
RRI	650.50 ± 9.70	565.63 ± 16.19	<.0001	yes	yes
RMSSD	13.89 ± 0.88	6.17 ± 0.77	<.0001	yes	
TP	1107.75 ± 131.81	305.98 ± 58.73	<.0001	yes	yes
HF	95.57 ± 13.73	21.49 ± 7.03	<.0001	yes	
LF/HF	150.04 ± 104.68	104.68 ± 46.39	<.0001	yes	yes
HFnu	0.20 ± 0.01	0.25 ± 0.02	0.013	yes	
CDM LF	16.22 ± 0.78	5.75 ± 0.86	<.0001	yes	yes
CDM HF	8.28 ± 0.57	3.35 ± 0.53	<.0001	yes	
CDM LF/HF	2.40 ± 0.09	1.79 ± 0.13	<.0001	yes	yes

RRI, mean R-to-R interval of the EKG, ms; RMSSD, the square root of the mean squared differences of successive normal-to-normal (NN) RRIs; TP, total R-to-R interval spectral power (0.003-0.4 Hz, ms^2); HF, RRI spectral power at the high frequency (0.15-0.4, ms^2); LF/HF, the ratio of LF (RRI spectral power at the low frequency (0.04-0.15 Hz, ms^2) to HF; HFnu, spectral power at the high frequency normalized to TP; CDM LF, amplitude of the LF oscillations by complex demodulation; CDM HF, amplitude of the HF oscillations. CDM LF/HF, ratio of the CDM LF and CDM HF. Data are means ± SEM.

Table 3. Heart-rate complexity variables associated with the need to perform life-saving interventions by ANN.

Variable	Non LSI (n=197)	LSI (n=65)	p value
ApEn	1.10 ± 0.02	0.93 ± 0.04	<.0001
FDDA	1.13 ± 0.01	1.07 ± 0.01	<.0001
DFA	1.35 ± 0.03	1.07 ± 0.05	<.0001
SOD	0.15 ± 0.00	0.20 ± 0.01	<.0001
StatAV	0.82 ± 0.01	0.95 ± 0.01	<.0001
FW	52.59 ± 0.93	60.84 ± 1.17	<.0001
DisnEn	0.64 ± 0.01	0.55 ± 0.01	<.0001

ApEn, approximate entropy; FDDA, fractal dimension by dispersion analysis; DFA, short-term correlations within the RRI by Detrended Fluctuations Analysis; SOD, similarity of distributions; StatAV, signal Stationarity; FW (%), forbidden words; DisnEn, normalized signal distribution entropy. All variables are unitless. Data are means ± SEM.

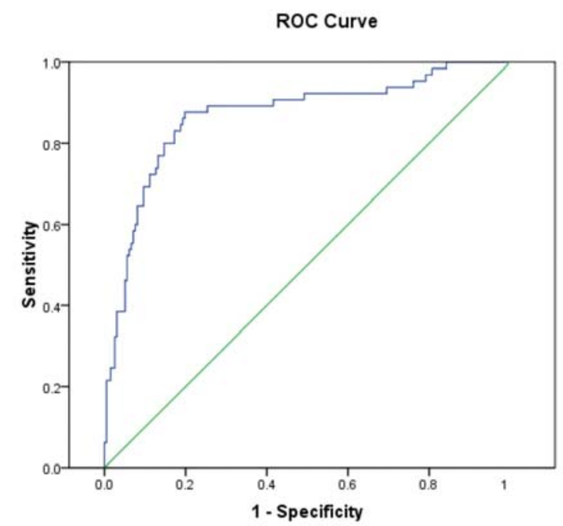

Fig. 1 ROC curve for model derived by ANN for identification of patients who received LSIs using EKG variables alone. Area under the curve (AUC) = 0.868; 10-fold cross validation; standard error 0.028. Asymptotic significance was 0.001; and the lower and higher asymptotic 95% confidence intervals were 0.812 and 0.924, respectively.

Observations

Data from 192 prehospital trauma patients and 70 emergency room patients (n=262) patients were included in the study. 65 patients received a total of 88 life-saving interventions (LSIs).

LSIs included: intubation (n=61), cardiopulmonary resuscitation (n=5), cricothyroidotomy (n=2), emergency blood transfusions (n=4), and decompression of pneumothorax (n=16).

From a clinical standpoint LSI and non-LSI patients were indistinguishable with respect to age, sex, mechanism of injury, heart rate, or blood pressure (Table 1). However HR and SAP were statistically different among the groups.

Sixteen of the EKG-derived vital signs listed in (Tables 2 and 3) separated the LSI and NonLSI patients. Note, for the Frequency-domain variables TP, HF, LF/HF, HFnu listed in Table 2, 200-beat datasets maybe too short for methodological validity.

ANN identified patients who received an LSI based on EKG-derived data alone with a significant and clinically relevant degree of accuracy (Fig. 1).

Conclusions

This retrospective analysis suggests that the need to perform LSIs could be predicted in entirely automatic fashion, pending further improvements in computerized waveform analysis, signal processing, and transmission.

Potential applications of our approach include development of personal diagnostic and monitoring systems to be used for remote assessment and triage of combat casualties, in automobile accident alert systems and on patients in austere environments and mass-casualty settings.

Our approach could also serve as an evidence-based decision assistance tool helping medical providers distinguish patients in imminent danger of dying during times when changes in their traditional vital signs are non-informative.

This material has been presented at the International Conference on Artificial Intelligence in Medicine and accepted for publication in Lectures in Computer Science, 2009.